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MARKET SEGMENTATION: A MANAGERIAL PERSPECTIVE

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Summary:

Market segmentation is simple in concept but difficult in application. This paper offers a new, managerial view of the segmentation process and offers some modifications to standard segmentation practice that are necessary for decision-making.

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Since the pioneering work of Wendell Smith,¹ the concept of market segmentation has grown in its importance and relevance to marketers. In fact a special section in the August 1976 issue of the Journal of Marketing Research was devoted to segmentation issues and research.² The concept simply postulates that because consumers are different, different marketing programs may be required to yield desired organizational goals. The contribution of market segmentation theory should not be taken lightly.

Despite the usefulness of market segmentation to decision-making and research, some problems continue to exist and others have been spawned by researchers' overenthusiastic attempts to merge the original concept with recent areas of marketing concern such as consumer behavior and multivariate data analysis. This paper represents an attempt to resolve some of the problems associated with the application of a simple concept to a complex market place as well as to highlight important strategic implications.

In this paper we offer a conceptual representation of the disaggregative-aggregative process of segmentation and the steps required to operationalize the procedure. This new way of conceptualizing market segmentation should prove useful to both the researcher with a large data bank as well as the manager with an intuitive feel for the market that can be quantified using subjective estimates.

Segmentation Strategy: A Conceptual Representation

In Smith's original work, great effort was made to delineate between two alternative strategies: market segmentation and product differentiation.

The former was described as a merchandising strategy and the latter as a promotional strategy. Although most scholars have recognized a convergence of these two concepts (perhaps "products are differentiated from your other products or your competitors' products because different market segments exist"), Smith's conceptual definition that market segmentation is the "disaggregation of demand" serves as an ideal by which all applications can be judged. By "demand" Smith refers to the demand function considered by economists; this is the response of demand to marketing variables such as price, advertising, etc.

One of the major problems associated with the practice of market segmentation is the measurement of demand response. Although there have been exceptions,³ most scholars have used surrogate measures of demand response.

Since an exhaustive discussion of proxy measures of response is not the purpose of this paper, suffice it to say that many of the traditional bases of segmentation, such as level of product consumption (e.g., heavy half⁴) should be seriously questioned. It can be shown, for example, that demand response for a brand is a function of the total product consumption response and well as the market share response. For a frequently purchased, low-priced supermarket item McGinn⁵ has reported far greater responses to pricing and advertising by light and medium users when compared with heavy users. In a proprietary unpublished study, we have found similar cases in examination of intention to switch in the automobile motor oil market.

Given the inherent weaknesses with the heavy half approach a wide variety of alternative bases exist; these may include current brand

perceptions,⁶ benefits sought,⁷ or intended response to new product options.⁸ New methodologies such as conjoint analysis offer additional promise in deriving demand functions. While these new bases and methods of segmentation may offer more face validity than heavy half measures, true validation studies are notably absent. The testing of these surrogate measures is one of the most needed areas of market segmentation research.

If we presume to be able to develop proxy measures of demand response, an important consideration that follows is the method by which individuals will be grouped into segments and the determination of the resultant segmentation strategy. Although Smith essentially views segmentation as a disaggregative process, Claycamp and Lassy⁹ offer convincing evidence that segmentation should be viewed as an aggregative process because of measurement problems, pricing policy constraints, media constraints, etc. Our view is that segmentation should essentially be considered a disaggregative process followed by an aggregative process and responsive to the cost-benefit issues inherent in the level of disaggregation or aggregation. In spirit, this is similar to the work of Martin and Wright¹⁰ who propose a profit-based alternative to the simple AID clustering process. Recent advances in normative segmentation theory by Mahajan and Jain¹¹ and Tollerfson and Lessig¹² are also compatible with our method.

An overview of our alternative plan of segmentation is shown in Figure 1. As can be seen the key element is a segment-market mix matrix. We shall first discuss the nature of the matrix and then consider related issues of data disaggregation, parameter estimation, optimization procedures, and marketing mix reduction methods.

The Segment-Marketing Mix Profit Matrix

In order to formulate a conceptual alternative to previous methods of deriving a segmentation strategy, it is first necessary to specify the objective of the strategy. For most private sector firms it is reasonable to consider profit as the primary objective although our basic measure can and will later be adapted to public sector market segmentation. Therefore the net benefit associated with a marketing mix j is Z_j where:

$$Z_j = \sum_{i=1}^{ns} \pi_{ij} - FC_j$$

where

π_{ij} = gross profit obtained from offering marketing mix j to segment i

FC_j = fixed cost to the firm associated with offering marketing mix j

and

$$\pi_{ij} = N_i C_j D_{ij} P_{ij}$$

where

ns = number of segments

N_i = number of consumers in segment i

C_j = contribution (i.e., price - variable cost) to the firm of each unit purchase by each consumer in segment i of marketing mix j

D_{ij} = primary demand (average demand of product class) by segment i when marketing mix j is offered

P_{ij} = probability of purchase of product defined by marketing mix j by segment i consumers

Our objective is therefore one of selecting a subset of all feasible marketing mixes such that the sum of the Z_j will be maximum.¹³ Although the estimation of the π_{ij} values has been facilitated by the decomposition

the components of π are measured with error. By making the assumption that the component errors are uncorrelated, π_{ij} may simply be interpreted as "expected gross profit." Where errors are large, a sensitivity analysis of π_{ij} is warranted.

Our first step in segmentation analysis is to disaggregate the market into groups that have very similar responses of π_{ij} to marketing variables. This suggests that primary demand response and probability of purchase response will be similar for all consumers within a segment. Although this may produce large numbers of segments, a subsequent "aggregation" process will alleviate this problem.

Segmentation strategy involves the selection of a subset of marketing mixes from all available marketing mixes. We need to make the assumption however that only one marketing mix can be used on each segment; this is reasonable if segments have been disaggregated to the point of high homogeneity (low overlap on determinant variables). Table 1 shows a hypothetical example of 3 alternative marketing mixes and 4 segments. Entries in the matrix are gross profit, π_{ij} , figures that are expected to result if marketing mix j is offered to segment i ; also shown is the fixed cost vector associated with each marketing mix. Numbers were selected to facilitate optimization by inspection.

As can be seen, segment II reflects the most sensitivity to the alternative marketing mixes and consequently marketing mix 4 is justified (profit = 15000 - 3000 = 12000). Segment IV, on the other hand, is almost totally unresponsive in profit to the marketing mix. It can be seen that the only other marketing mix addition necessary for optimization is mix 3 in spite of the fact that it is less than optimal for segments I

and III. Although Segment I is more profitably captured with mix 1, the increased gross profit (\$1000 compared to mix 6) does not offset the increased fixed cost of \$3000. Thus the changes in contribution margin, primary demand, and/or probability of purchase from mix 1 compared to mix 6 are not large enough to warrant an additional marketing mix.

We can consider this an aggregation of segments I, III, and IV since the same marketing mix (Number 6) will be used for these segments. Although standard criteria for segmentation such as heterogeneity, accessibility, substantiality are related to the matrix, these factors are far more difficult to quantify and relate to the overall profit function.

This conceptual method offers a new and unique perspective to market segmentation. Consider the following implications:

1. a marketing mix may be selected even though it is not optimal for any segment. (In the example only segment II receives an optimal mix.)
2. segments are "aggregated" because they respond most to the same marketing mix of those selected. They may, in fact, have different response patterns. (Note that segments I, II, and IV are drastically different but marketing mix 6 is justified for all three segments. This is totally compatible with the work of Tollefson and Lessig¹⁴ who argue that segments should not be aggregated on the basis of response elasticities.)
3. factors such as selective accessibility are automatically considered and quantified. For example, if the market for one product variation is exposed to a wide variety of media, this in turn will be reflected in large numbers of homogeneous

segments. Thus the marketer will weigh the profit potential against the large fixed cost associated with a mass marketing strategy or the accumulation of multiple fixed costs associated with many marketing mixes differing in media schedules.

4. there is no longer any need (or relevance) to specify target markets versus non-targets. Traditional non-target groups essentially reflect a low profit potential and thus receive little weight in the determination of the appropriate marketing mixes.

Segment Formation: A Disaggregative Process

Segment formation can easily be accomplished using cluster analysis or a similar procedure. It should be apparent from our previous discussion that the number of segments formed need not cause concern; some segments will subsequently be aggregated by procedures that deal with the segment-marketing mix profit matrix.

It is important, however, that segments be formed on the basis of determinant variables. By determinant variables we mean those measures that lead to some way (analytically or subjectively) of deriving the response of the segment (in terms of D and P) to the various marketing mixes. Thus variables that include attitudinal measures, conjoint analysis measures, media exposure, shopping habits, consumption, etc. will be more determinant than demographic measures.

The disaggregation process should proceed as far as the data will allow. Because large number of segments can result if the data set is large (in order to achieve high intra-segment homogeneity), the number

of respondents in the data bank will heavily influence the level of disaggregation that we can utilize.

Parameter Estimation

It may be argued that the success that will result from applying this method is heavily dependent upon the inputs that lead to the π_{ij} values in the matrix. Stochastic behavior within a segment results for two primary reasons: (1) the heterogeneity of consumers within the segment, and (2) the stochastic nature of the consumer himself. In the first regard the high level of disaggregation should prove helpful as consumers within a segment will be very similar. The second problem is highly controversial; some argue the inherent nature of man is stochastic while others argue that man may be deterministic but appears stochastic because of our inability in measurement. In any event, improved measurement will undoubtedly help in deriving the expected D_{ij} and P_{ij} . Nevertheless, the prediction of the response of consumers (either the aggregate group or subgroups) is a problem faced and resolved by all marketers; it is not reasonable to attribute our ability or inability to do so to a method of market segmentation.

The remainder of the terms that determine π_{ij} should be relatively easy to estimate. π_i can be derived from the relative size of the clusters and C_j is determined by the price (defined by the marketing mix) and variable cost. Appendix A details a sample calculation of a hypothetical value shown in Table 1.

Optimization Procedures

The matrix formulation shown in Table 1 was designed to facilitate optimization by inspection. Clearly the matrix itself adds greatly to our ability to do so.

For many cases, particularly those where we have a great deal of data (thereby yielding large numbers of segments) and large numbers of alternative marketing mixes, a solution by inspection may not be feasible. In this case the application of 0,1 integer programming will provide the necessary solution.¹⁵ Using integer programming one can easily include constraints that will satisfy Mahajan and Jain's objections to current approaches to segmentation:

- (they) do not allow the imposition of managerial and institutional constraints in the development of market segments;
- (they) provide static segment composition, thus precluding the examination of most probable segment compositions which may be more efficient in satisfying constraints; and
- (they) allocate resources to segments given a priori, rather than develop segments in conjunction with resource constraints.¹⁶

. 0,1 programming version of this problem is shown in Appendix B.

Reducing the Combinations of Marketing Mixes

One of the problems with the above method is the sheer number of available marketing mixes. Consider for example a firm who determines 5 alternative product variations, 4 potential methods of distribution, 6 pricing alternatives, 3 alternative media schedules, and 7 different advertising messages; the number of marketing mixes exceeds 6000 when we consider all possible combinations. This would undoubtedly tax any integer program not to mention the excessive number of parameter esti-

lates required. Fortunately, we can reduce the number of mixes that we consider by using traditional methods of market segmentation research. Several caveats are in order. The rationale behind these will be discussed.

The most obvious way to reduce the number of feasible marketing mixes is to eliminate those that management considers unacceptable. A firm may, for example, choose not to consider any mix that incorporates a particular form of distribution channel. The rationale may include the incompatibility with the company image or perhaps a high start up cost. In addition to economic considerations, ethical constraints may reduce the number of feasible mixes to a manageable number.

Another method is to see if some components of the mix seem to fit well with other components. For example, if we find for one product alternative that there is clearly one best media schedule, then it may not be necessary to consider other media schedules with this product and other variations. Thus we can eliminate from consideration the other 7 media combinations with 6 pricing alternatives, 7 advertising messages, and 4 methods of distribution given this product variation; this results in a reduction of 1176 mixes from the potential matrix. Although this reduction process may not yield an overall optimum, the reduced number of estimates required for the matrix will in part compensate for the minor loss.

Therefore an important component of market segmentation research is to see what components of the marketing mix go together with other components. In the literature, however, we see many attempts to relate some basis for segmentation to demographic characteristics of the population.¹⁷

As Frank, Massy and Wind¹⁸ explain, these demographic descriptors may serve as a link between measures of response to the marketing mix. In the previous example, if we find demographics to be significantly related to response to a product variation as well as to media, it may be possible to establish a relationship between response to a product variation and media readership.

In the absence of any specific way to establish this relationship, we have tested the viability of this approach using a test heavily biased in favor of this method.¹⁹ Using a mail panel from Market Facts who responded to a questionnaire about automobile motor oil, the data were split into two groups: an analysis group and a holdout group. On the basis of finding significant relationships between demographic variables and a segment base as well as media readership in the analysis group, our attempts to derive the relationship between media usage and the segment base produced equivocal results. Discriminant analysis in conjunction with a Bayesian classification analysis was used, and thus our efforts were considerably more sophisticated than a simple matching of demographic profiles.

The conclusion that we reach is that whenever possible data concerning response to the marketing mix (e.g., product response, media usage, shopping habits, etc.) should be collected simultaneously. A heavy reliance on demographic or other measures to establish a linkage may produce unsatisfactory results.

The second problem that may occur when the interrelationships between marketing mix variables are explored relates to the method of analysis. With the widespread diffusion of multivariate techniques into

our discipline one would, for example, be highly tempted to use regression analysis to establish a relationship between independent variables of frequency of distribution outlet used and dependent variables such as price sensitivity or media exposure.

The problem associated with most multivariate methods is that they are in some way based on a measure of correlation which removes the mean level and variance of the variables. An illustrative example has been chosen to show the impact of decisions based on a correlation measure.

Table 2 indicates simple correlations for the Market Facts sample (previously described) between a proxy measure of response to a new automotive oil product (undisclosed for proprietary reasons) and readership of 3 media vehicles. As can be seen the highest positive correlation was between response and readership of Road and Track; both Better Homes and Gardens and Reader's Digest were negatively correlated with response. On this basis one might decide to advertise in Road and Track. However, the positive correlation means only that those respondents who have a higher than average response tend to exhibit a higher than average readership of Road and Track. Therefore if the average readership of Road and Track is low, the low probability of exposure would suggest that Road and Track is a poor choice.

Table 3 shows simple cross classifications between our proxy measure of response and readership. With Better Homes and Gardens, one can expect double the number of readers in the high response group. Reader's Digest will produce approximately four times the number of readers in the high response group when compared with Road and Track. These findings result from the much higher readership levels of Better Homes and Gardens

and Reader's Digest. Although we have ignored cost considerations, the impact of cost on suitability of correlational measures is discussed elsewhere.²⁰

Correlational methods may also be unsuitable elsewhere. For example, if we find that response to a low price is related to an AIO (factor or raw score) score measuring "concern for the environment," this does not necessarily imply that our low-priced product should have environmental appeals. It may be that concern for the environment has such a low mean score that only a very small fraction of the population have a real concern for the environment. Correlation has removed this information from our analysis. The suggestion of all this is that cross products or simple cross-classification may be the most effective in designing integrated marketing mixes for consideration by our segmentation strategy algorithm.

Revision of Segmentation Strategy for the Not-For-Profit Sector

Although segmentation of the market by a "not-for-profit" firm can follow the conceptual representation of the segment-mix profit matrix previously discussed, one adjustment is important. The critical difference between the profit and "not-for-profit" sector in terms of market segmentation is the objective function. For the private sector, the profit objective (Z) is directly proportional to overall demand or the sum of individuals' demands multiplied by the contribution margin C .

In the not-for-profit sector, the objective is a more complicated and relates to "social welfare" or whatever the organizational goals encompass. Thus a group assembled to deal with malnutrition might state: "Our goals are to reduce malnutrition among those individuals for whom

malnutrition has particularly serious consequences." The above statement indicates that the organization is particularly concerned with individuals who both have a protein deficiency and for whom this deficiency has serious consequences. For example, even short-term protein deficiency has been shown to have irreversible consequences for young children as well as pregnant and lactating mothers.²¹ Therefore the value of the conversion of an individual to a higher protein diet should be dependent upon the individual's protein deficiency (defined as recommended level minus current consumption) as well as a weighting factor reflecting the gravity of this deficiency. Therefore, efforts should be targeted toward segments both high in value and responsiveness. In terms of our previous conceptual framework, this can be easily accomplished by using V_{ij} (substituted for C_j) to represent the average value of a unit of consumption of the product associated with marketing mix j by consumers in segment i :

$$Z_j = \left[\sum_{i=1}^{ns} w_i V_{ij} D_{ij} P_{ij} \right] - FC_j$$

Thus variables pertinent to both value and response should be used to cluster consumers into segments.

This approach is truly dynamic since response will yield greater consumption and therefore less value; the objective is, of course, to lower the levels of V so that marketing beyond some maintenance level becomes unnecessary. This example also affords an interesting additional perspective into the use of demographic variables since the consequences of malnutrition are defined accordingly. Value-response segmentation will apply equally well to other social marketing programs such as birth

control. Once again the organizational objectives play a major role in the determination of the value base ("do you want to reduce the number of births or reduce the number of unwanted births?").

Conclusions

An alternative and managerially appealing view of segmentation is one of disaggregation in purchase response variables followed by aggregation based on marketing mixes to be used in segmentation strategy. In addition to being most relevant to profit, this procedure avoids such considerations as targets versus non-targets, substantiality, homogeneity, and accessibility, which defy simple quantification for the manager's objective function. With one simple modification this method should prove equally applicable to the "not-for-profit" marketer as it is to the private sector.

In order to limit the number of marketing mixes to be considered marketers will find it useful to turn to the traditional segmentation approach of measuring the relationship between proxy variables of market response. To do this effectively, however, requires that one measure the variables simultaneously and not exclude mean levels from the analysis. Traditional measures based on correlation will not prove to be satisfactory.

There exist several limitations with this approach to market segmentation. Estimation of the segment-marketing mix profit matrix can be demanding, and yet, specification of parameters necessary for estimation will be required with any marketing decision. By specifying discrete levels of the marketing mix and reducing the number of mixes to be con-

sidered, we must accept the risk of not reaching an overall optimum.

In practice, this should result in a very small deviation from maximum profit, and the method does seem more appealing than optimization using microeconomics analytical techniques which impose several restrictions on demand functions and cost structures.

ENDNOTES

1. Wendell Smith, "Product Differentiation and Market Segmentation as Alternative Marketing Strategies," Journal of Marketing, Vol. 21 (July 1956), pp. 3-8.
2. See entire issue but particularly Yoram Wind, "Issues and Advances in Segmentation Research;" Vijay Mahajan and Arun K. Jain, "An Approach to Normative Segmentation;" and John O. Tollefson and V. Parker Lessig, "Aggregative Criteria in Normative Segmentation Theory."
3. John L. McCann, "Market Segment Response to the Marketing Decision Variables," Journal of Marketing Research, Vol. 11, No. 4 (November 1974), pp. 399-412.
4. Dick Warren Twedt, "Some Practical Applications of 'Heavy-Half' Theory," Word of Mouth Advertising, Johan Arnit, editor, Advertising Research Foundation, 1967.
5. Same as reference 3 above.
6. Richard M. Johnson, "Market Segmentation: A Strategic Management Tool," Journal of Marketing Research, Vol. 3 (February, 1971), pp. 13-18.
7. Russell I. Haley, "Benefit Segmentation," Journal of Marketing, Vol. 32 (July, 1968), pp. 30-35.
8. Vithala Rao and Frederick Winter, "An Application of the Multivariate Probit Model to Market Segmentation and New Product Design," Journal of Marketing Research, Vol. 13 (August 1976), pp. 361-368.
9. Henry J. Claycamp and William F. Massy, "A Theory of Market Segmentation," Journal of Marketing Research, Vol. 5, No. 4 (November 1968), pp. 388-394.
10. Claude R. Martin and Roger L. Wright, "Profit-Oriented Data Analysis for Market Segmentation: An Alternative to AID," Journal of Marketing Research, Vol. 11, No. 3 (August 1974), pp. 337-400.
11. Same as reference 2 above.
12. Same as reference 2 above.
13. In actuality, the π and FC streams will continue over time. Thus, it will be necessary to discount anticipated future quantities into present values of π and FC.
14. Same as reference 2 above.

15. Frederick W. Winter and Charles E. Blair, "A 0,1 Programming Approach to the Strategy of Market Segmentation," working paper.
16. Same as reference 2 above.
17. Ronald E. Frank, "Market Segmentation Research: Findings and Implications" in Frank R. Bass, Charles W. King, and Edgar A. Pessier, eds., The Application of the Sciences to Marketing Management (New York: Wiley and Sons, 1968), pp. 39-65.
18. Ronald E. Frank, William F. Massy, and Yoram Wind, Market Segmentation (Englewood Cliffs, NJ: Prentice-Hall, 1972), pp. 15-19.
19. This procedure is described in detail in Frederick W. Winter, "Match Target Markets to Media," Journal of Advertising Research, forthcoming.
20. Ibid.
21. Kevin S. Scribshaw and John F. Gordon, Malnutrition, Learning, and Behavior (Cambridge: M.I.T. Press, 1968).

Figure 1

Overview of the Segmentation Process

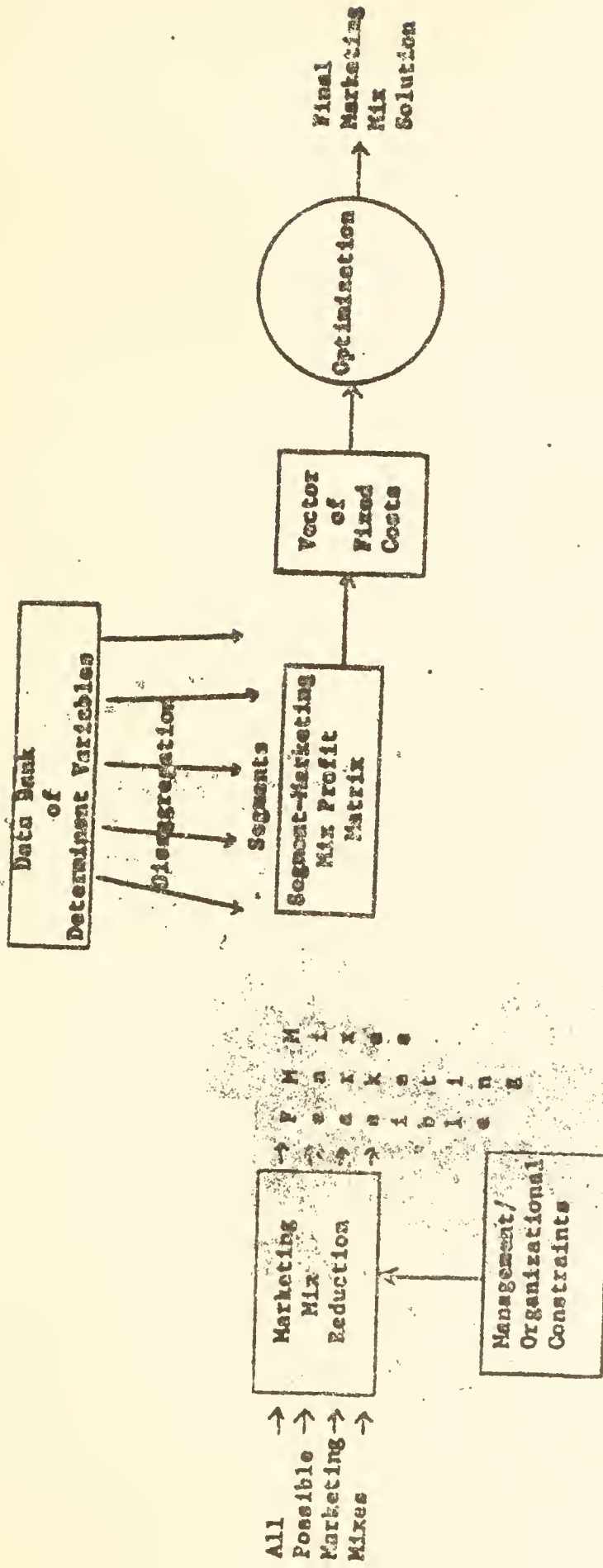


Table 1

Hypothetical Segment-Marketing Mix Profit Matrix

		Aggregate Market					
		Market Segments					
		I	II	III	IV	Fixed Cost (FC)	
Alternative Marketing Mixes	1	7000 ^a	2000	0000	7000	3000	
	2	2000	3000	1000	7000	6000	
	3	2000	4000	0000	7000	3000	
	4	2000	15000	0000	5000	3000	
	5	2000	2000	0000	7000	2000	
	6	6000	3000	5000 ^b	7000	3000	
	7	4000	1000	9000	7000	6000	
	8	2000	4000	0000	7000	4000	

^a Numbers in matrix represent gross profits before fixed costs (π).

^b For an example of how this number might be estimated refer to Appendix A.

Table 2

Simple Correlations Between Response to a
New Product and Media Readership

	Frequency of Media Readership (Times per year)		
	<u>Load and Track</u>	<u>Better Homes & Gardens</u>	<u>Reader's Digest</u>
Response to a New Product	.09	-.27	-.12

n = 258

Table 3

Cross Classifications Between Response to
a New Product and Media Readership (n=258)

Readership of Road and Track

	None or Infrequent	Frequent	
Response	Low	154	13
	High	70	13

Readership of Better Homes and Gardens

		None or Infrequent	Frequent
Response	Low	74	93
	High	60	31

Readership of Reader's Digest

	None or Infrequent	Frequent	
Response	Low	45	122
	High	31	60

APPENDIX A: SAMPLE DERIVATION OF A π ENTRY

We note in Table 1 that we expect \$9000 gross profit (π) by offering marketing mix 7 to segment III. A sample calculation is shown for this hypothetical problem.

I. Background: Assume this produce class involves a convenience type of item where the choice of the distribution outlet determines the brands from which the consumer will choose. Also the product is assumed to be one in which 2 advertising exposures are required to encourage trial. After trial, advertising will have little effect.

II. Hypothetical Marketing Mix 7:

- A. Product profile--
 - 1. Resealable container
 - 2. lemon-flavored
 - 3. 20¢ selling price (50¢ from manufacture to distributor, 20¢ unit cost)
 - 4. low calorie formulation
- B. Distribution--limited to XYZ Drug Stores, Inc.
- C. Media--12 insertions in Medium ABC

III. Hypothetical Description of Segment III:

- A. Segment Size--40000 consumers
- B. Average Demand of Product Class--5 units
- C. Percent of Product Class Purchases Made at XYZ--40%
- D. Average Number of Exposures to Medium ABC (12 possible)--3
- E. Index From Probit-conjoint Analysis of Product Attributes
(IIA, above) = -.13 (see endnote 3 for a reference describing how this technique can be used to estimate probability of

purchase). This translates into a .45 probability of purchase based on product attribute.

IV. Calculation of π :

For π calculation,

$$N = 40000$$

$$D = 5 \text{ (assumed to be unresponsive to marketing mix)}$$

$$C = .50 - .20 = .30$$

$$P = (\text{Probability of Buying Product Based on Attributes})$$

$$\times (\text{Probability of Receiving 2 or more Exposures})^a$$

$$\times (\text{Probability of a Purchase at XYZ})$$

$$= .45 \times .84 \times .40 = .15$$

$$\pi_{7,III} = (40000)(5)(.3)(.15) = \$9000$$

^aDerived from binomial probability distribution.

APPENDIX B

A 0,1 integer programming formulation of the problem can be described as follows:

$$\text{Max } \left\{ \sum_{j=1}^{nm} \sum_{i=1}^{ns} \pi_{ij} x_{ij} - \sum_{j=1}^{nm} FC_j w_j \right\} \quad nm = \text{number of possible marketing mixes}$$

subject to:

$$\sum_{j=1}^{nm} x_{ij} \leq 1 \text{ for all } i$$

$$x_{ij} - w_j \leq 0 \text{ for all } i, j$$

$$x_{ij} = 0 \text{ or } 1 \text{ for all } i, j$$

$$w_j = 0 \text{ or } 1 \text{ for all } j$$

If for any i , $x_{ij} = 1$, then marketing mix j should be offered. A 0,1 analysis of Table 1 would reveal $x_{II,4} = 1$, $x_{I,6} = 1$, $x_{III,6} = 1$, $x_{IV,6} = 1$. All other x values would be 0.

Details of this procedure can be found in the reference cited in endnote 15. Extensions of the formulation are shown and limitations of the procedure are discussed.



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